COMPETITION IN THE CREDIT RATING INDUSTRY

HOW COMPETITION BETWEEN RATING AGENCIES AFFECTS RATING QUALITY

FRANSISKA ASPEGRÉN

PHILIP JOHANSSON

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Competition in the Credit Rating Industry: How Competition between Rating Agencies affects Rating Quality

Abstract:

Higher levels of competition between credit rating agencies on an industry-year level have previously been shown to decrease the rating quality of incumbent firm credit ratings after specific changes in the credit rating industry. We successfully replicate this research and extend it empirically, finding no evidence that this correlation holds for the time period 2010-2016. Specifically, we look at how the rating quality of long-term firm credit ratings issued by Standard & Poor's is affected by competition quantified in two ways, Fitch Ratings market share and the Hirschman-Herfindahl Index. We conclude that our results indicate a positive trend towards more informative firm ratings of higher quality, as the level of competition does not have a significant impact on rating level and informativeness.

Keywords:

Credit ratings, Credit rating agencies, Rating quality, Competition, Reputation

Authors:

Fransiska Aspegrén (24229)
Philip Johansson (24209)

Tutors:

Adam Altmejd, Postdoctoral Fellow, Department of Finance

Examiner:

Adrien d'Avernas, Assistant Professor, Department of Finance

Bachelor Thesis
Bachelor Program in Business & Economics
Stockholm School of Economics

1. Introduction

The financial crisis of 2008 brought credit rating agencies and their role as information providers to the forefront of public discourse. Firm and bond ratings influence the cost of funding, capital structure policies, and are the basis for contractual triggers. Market participants and even regulators have for a long time relied on ratings in assessing risk (Sangiorgi and Spatt, 2017). There are widely discussed sources of friction in the accuracy of ratings, including the effects of competition between rating agencies on rating quality (Becker and Milbourn, 2011). We however empirically show that during the years 2010-2016, competition in the credit rating industry does not significantly impact rating quality. This is deemed to be a positive development, as the high and consistent quality of credit ratings is an essential factor for the proper functioning of the financial system (Stahl and Strausz, 2017).

The business model of rating agencies, known as the issuer-pay model, is a well-documented source of friction in the determination of ratings. Issuers (entities) of bonds, as opposed to subscribers, pay for the issuance of their ratings. The industry is dominated by only three credit rating agencies, Standard & Poor's (S&P), Moody's, and Fitch Ratings (Fitch), which makes it vulnerable for potential rating inflation, in which the agencies provide ratings that are high in order to attract issuers (Sangiorgi and Spatt, 2017). This has been investigated in both empirical and theoretical papers, such as Becker and Milbourn (2011). In their empirical paper studying the time period 1995-2006, they find that increased competition, measured as market share by Fitch, leads to lower quality ratings by the incumbent firms S&P and Moody's in the market for corporate bonds.

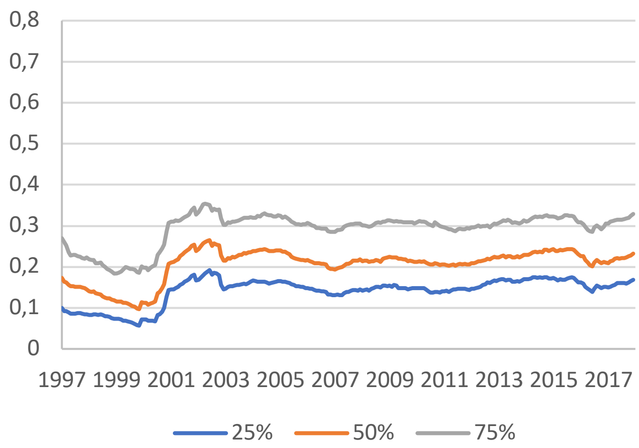
In this paper, we examine whether the negative effects of competition on rating quality shown by Becker and Milbourn (2011) are specific for the time period 1995-2006, or if the negative effects still persist in a later time period. The question addressed is how the rating quality of firms (issuers) rated by S&P has been affected by competition in the time span 2010-2016. Rating quality is measured in two dimensions, ability to classify risk and rating informativeness. It is in the interest of the users of credit ratings to have stable rating levels and risk classifications over time. Following Becker and Milbourn (2011), we therefore treat an overarching increase in rating level (i.e. rating inflation) as a lessening of quality. Rating informativeness is measured as a firm ratings ability to accurately predict default. Our initial competitive measure is Fitch market share, measured as the fraction of bond ratings issued by Fitch in a specific industry and year. We also include a second measure of competition, the Hirschman-Herfindahl Index (HH-Index), calculated as the square of the sum of the market shares of Fitch, Moody's, and S&P. The effects of competition on rating quality is captured through different intensities of competition, as the market share varies considerably between industries. We start with a replication of Becker and Milbourn's (2011) results before examining the later time period 2010-2016, testing the hypotheses that 1) increased competition leads to higher rating levels and 2) increased competition leads to a decline in rating informativeness.

The time period 2010-2016 differs from 1995-2006 in several ways. Becker and Milbourn (2011) use Fitch's market share as their independent variable, which was growing explosively at the time and therefore most accurately represents the big shift occurring in the credit rating industry. In 2010-2016, Fitch is however no longer a novel challenger to the incumbents S&P and Moody's. It was added to the Lehman Index in 2005, was used in regulation as a tiebreaker, and has reached a relatively stable market share within individual industries, as seen in Figure 1 (Becker and Milbourn, 2011). As we believe that the choice of measure of competition should be motivated by the current market conditions, we also use the HH-Index, to not potentially exclude any significant market changes not captured by Fitch's market share alone. The time period we study also follows the financial crisis of 2008, for which the credit rating agencies were partially blamed for inflated ratings in the structured product market (Financial Crisis Inquiry Commission, 2011). As a consequence of the financial crisis, the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank Act) was implemented in 2010. It mandated the removal of regulatory reference to ratings and made the agencies liable for their ratings (Sangiorgi and Spatt, 2017). Although these were later not rigorously implemented, these regulatory changes initially resulted in the credit rating agencies broadly lowering their ratings and issuing downgrades that were less informative (Dimitrov et al. 2015, Partnoy, 2017). Taking these factors into consideration, we believe that it is of interest to explore whether the effects of competition on rating quality are present in a time period subject to different market conditions than those examined by Becker and Milbourn (2011).

Using a dataset with roughly 30,000 US corporate firm ratings and over one million bond ratings to calculate Fitch market share and HH-Index, we perform a series of ordinary least squares (OLS) and ordered probit regressions between firm credit rating and the two measures of competition. Fixed effects for industries, years, and firms, as well as firm characteristics are included in the regressions to rule out possible omitted variable bias, such as time-trend and cross-industry explanations. We successfully replicate Becker and Milbourn (2011) results for 1995-2006, finding that increased competition from Fitch results in lower quality ratings in the two dimensions, both as higher rating levels and as a lower ability of the ratings to accurately predict defaults. Contrasting these findings, the regressions using data from 2010-2016 between firm ratings and our measures of competition show no significant correlation. This implies that competition does not affect rating quality and that the effects shown by Becker and Milbourn (2011) most likely are specific to the time period they investigate.

This paper is organized as follows. Section 2 provides an overview of the existing literature. In section 3 we give a comprehensive overview of the credit rating industry. In section 4 we present the data and our methodology, followed by our results in section 5. The discussions of findings are found in section 6 and conclusions in section 7.

Figure 1
Evolution of Fitch's market share by industry and month. Fitch's market share is computed by dividing the number of bond ratings assigned by Fitch by the sum of the number of bond ratings assigned by S&P, Moody's and Fitch. Bond affirmations are excluded. Rolling 24-month averages in the 25th, 50th, and 75th percentile industries are used to estimate the trends.



2. Literature Review

The issuer-pay model creates friction when the buyer of the rating (the issuer) is different from the final user of the rating (the investors) (Sangiorgi and Spatt, 2017). Although there are benefits over an investor-pay model, both in that the problem of information resale is resolved and that the certificates act as a signalling device in the market, rating agencies are faced with a blatant conflict of interest (Stahl and Strausz, 2017). Issuers demand high ratings, which could naturally lead credit ratings agencies to maximise profits by overrating issuers. Credit ratings agencies however claim that reputational concerns regulate their behaviour, stating that issuers will only pay for ratings if investors believe they are communicating something of value (Pacces and Romano, 2015). Bolton et al. (2012), Pacces and Romano (2015), and others have found that reputation is not enough to hinder the incentive of profit maximisation in the industry, largely due to investor naivety and lack of sophistication.

Our paper builds on prior work concerning the effects of competition on the credit rating industry. Research on competition between rating agencies and its impact on rating quality is ambiguous, where papers, both theoretical and empirical, either conclude that increased competition leads to increased rating levels and lower informativeness, that there is no significant relationship between competition and rating inflation, or that the effects are uncertain.

Becker and Milbourn (2011) find in their empirical paper that increased competition in the credit rating industry, measured as market share by the new-entrant Fitch, leads to lower quality corporate firm ratings by S&P and Moody's. Using a data set from 1995-2006, they show that Fitch's market share, the variable used to capture the intensity of competition across industries, is correlated with higher firm and corporate bond ratings within those industries, and hence lead to rating inflation. Similarly, Bolton et al. (2012) find that the rating industry for structured products is less efficient when several firms conduct ratings compared to a monopoly, as rating inflation occurs due to "rating shopping", in which issuers shops around and pressure rating agencies for more favourable ratings. Furthermore, under the current issuer-pay model, rating agencies are more likely to inflate ratings when facing competition (Camanho et al. 2010). Findings also show that a firm with a rating by Fitch will often have been issued a higher rating by S&P and Moody's (Jewell and Livingston, 1999).

In contrast to this, Bae et al. (2015) finds no relationship between competition and rating quality. In their reexamination of Becker and Milbourn (2011), they simultaneously control for industry fixed effects and firm characteristics, arguing that the effects are driven by industry characteristics instead of competition. Sangiorgi and Spatt (2017) find that the effects of competition on equilibrium rating inflation are ambiguous, highlighting the discipling effect of reputation. In their model, low reputation is costly as rating agencies are concerned about their reputation relative to other agencies. A further potential reason for ambiguous findings is that the effects of competition on rating quality for larger credit rating agencies can be too small to detect, even if they are present (Bae et al. 2019). Other papers find that the trend towards stricter corporate rating standards have resulted in lower firm ratings over time, which indicates that credit rating agencies have become more conservative in their rating methodology and that competition is presumably not a driver of higher firm ratings (Blume et al. 1998, Baghai et al. 2014).

Reputation and rating shopping are the basis for most research examining rating quality. Bar-Isaac and Shapiro (2013) find that while credit rating agencies claim that reputation concerns regulate their behaviour, the true value of reputation actually differs over the business cycle due to varying economic fundamentals. They analyse a model where reputation is endogenous and show that when competition is high, reputational losses are lower, leading to weaker incentives to provide accurate ratings (Bar-Isaac and Shapiro, 2013). When the rated securities are complex, the incentives to inflate ratings are higher for rating agencies and rating shopping becomes more severe as competition increases (Mathis et al. 2009, Skreta and Veldkamp, 2009). In contrast, our research encompasses only corporate firm and bond ratings, where Moody's and S&P have a policy to rate all taxable corporate firms publicly issued in the US. The agencies will publish a firm rating regardless of if the issuer pays for it, meaning that both the incentives for and ability to shop for ratings decreases (Spatt, 2009, Becker and Milbourn, 2011).

Rating quality was found to have deteriorated leading up to the financial crisis, where agencies were later blamed for providing favourable ratings to risky structured finance securities (Financial Crisis Inquiry Commission, 2011). While structured products were severely downgraded following the financial crisis, the market for corporate bonds was relatively stable and the number of downgrades was low over time (Benmelech and Dlugosz, 2009). Furthermore, the Dodd-Frank Act, introduced in 2010 as a response to the crisis, has been shown to have had adverse effects on the accuracy and informativeness of bond ratings (Dimitrov et al. 2015). These effects are more pronounced in markets where Fitch held a lower market share. Examining data from 2006 to 2012, Dimitrov et al. (2015) find that the rating level of corporate bonds decreases, uncorrelated to their actual level of risk.

Given that the literature is divided, additional research is of importance. Corporate ratings are also of interest as the majority of recent research has focused on structured product ratings, where rating shopping is a more prevalent issue. We extend the work done by Becker and Milbourn (2011) by examining a new data set from 2010-2016 and adding an additional measure of competition, the HH-Index, to explore the effects of competition on firm ratings in the corporate credit rating industry after the financial crisis.

3. The Credit Rating Industry

A credit rating is an assessment of the creditworthiness of a firm or security, measured along a rating scale which differs slightly among the major rating agencies (White, 2013).[1] Two types of credit ratings are corporate bond ratings, which are issued for most publicly traded US bonds, and corporate firm ratings, provided to most US public firms with outstanding debt. The rating is used as a measure to predict the likelihood of default and the ability for a firm to repay its debt in the case of default (Becker and Milbourn, 2011). Firm ratings are either solicited or unsolicited, where unsolicited ratings are not purchased or paid for by the issuer. If a firm pays for its rating, non-public information provided by the firm is used in assessing its creditworthiness, while only public information is considered in unsolicited ratings. These ratings tend to be coarser and lower, and can act as incentives for firms to pay for their ratings in the future (Sangiorgi and Spatt, 2017).

The rating market structure is oligopolistic in nature, with three participants accounting for over 90% of ratings outstanding (U.S. Securities and Exchange Commission, 2018). This is partially the result of a regulatory framework which imposed entry barriers, as credit rating agencies needed to be "nationally recognized" to be certified by the Security and Exchange

[1] See Appendix 1 for the rating scale used by S&P for long-term issuer credit ratings.

Commission (SEC) as a “Nationally Recognized Statistical Rating Organization” (NRSRO). Achieving this without prior certification by the SEC is difficult, as reputation and credibility are integral parts of the industry. In 2006 the Credit Rating Agency Reform Act was passed to encourage entry into the industry by making it easier for smaller firms to register with the SEC. The number of NRSROs subsequently grew from five to ten.[2] The effect of the Act was however limited, with the market share for the three bigger agencies remaining largely unchanged and most of the new actors specializing in niche industries (Sangiorgi and Spatt, 2017).

References to ratings in regulation were commonplace in the United States up until the Dodd-Frank Act was implemented in 2010. The law limited the use of ratings in US regulation and mandated greater supervision of the agencies, with the hope that the risk of penalty, through lower pleading standards and an increased ease of sanctions, would improve rating quality (Sangiorgi and Spatt, 2017). Dimitrov et al. (2015) however show that the Act in the years 2010-2012 instead caused further deterioration in the rating quality of bonds, since the risk of costly legal action led credit rating agencies to lower ratings more than justified. Since the signing of the Act, Partnoy (2017) however shows that the laws pertaining to credit rating agencies have largely remained unimplemented. Although pleading standards are lower, only a handful of private cases have been brought against credit rating agencies for losses sustained during the financial crisis. Furthermore, provisions removed by the Dodd-Frank Act, which had previously allowed for the privileged treatment of the agencies, were later reinstated by the SEC. Credit ratings are also still relied on by many institutions to provide investment criteria (Partnoy, 2017). The impact of the Dodd-Frank Act on the credit rating industry has thus been hampered.

There are several measures that could be used to quantify competition within the industry. The SEC publishes annual information on the state of competition, based on the number of outstanding credit ratings for each rating agency. It however discloses that the relative number of ratings issued by each rating agency per period would be a better measure of competition. This is due to some agencies being established much earlier than others, who can therefore have rated bonds that were issued before the creation of the newer agencies (U.S. Securities and Exchange Commission, 2018). The HH-Index is also a commonly accepted measure of market concentration used in a variety of contexts, such as reviews of mergers and antitrust cases by the Department of Justice (U.S. Department of Justice and Federal Trade Commission, 2010). It is calculated by summing the square of the market share of each competitor in an industry. More competitive markets where each actor has a smaller market share will have a lower index value, while consolidated markets will have a higher index value, where 10,000 is the maximum value and represents a perfect monopoly. The HH-Index Inverse is also one of the key metrics used to measure industry concentration by the SEC in their Annual Report on NRSRO, where it is continuously concluded that the rating agency industry is concentrated across all rating categories (U.S. Securities and Exchange Commission, 2018).[3]

[2] Currently there are only nine NRSROs since Morningstar withdrew from the market on November 15, 2019 after an acquisition of DBRS.

[3] HH-Index Inverse represents the number of equally sized firms that replicate the level of concentration exhibited in a particular industry.

4. Data and Methodology

4.1 Data

4.1.1 Mergent FISD

Mergent FISD provides details of bond issuances for over 140,000 corporate, corporate Medium-Term Note, supranational, U.S. agency, and U.S. Treasury debt securities (Wharton Research Data Services, 2020). From Mergent FISD, we retrieve observations for over two million bond ratings, spanning from 1995-2017. The data is used to calculate the market share within a particular industry and year for the three largest credit rating agencies, which is in the extension subsequently used to calculate the HH-Index of an industry-year cell. The variables of interest include the credit rating a particular issue has received, the date of the rating, the rating agency that issued the particular rating, the North American Industry Classification System (NAICS) code of the issuer, the Committee on Uniform Securities Identification Procedures (CUSIP) number, as well as individual database issue and issuer IDs. Bond ratings are matched with their respective NAICS code using the database issuer IDs. Issuers with missing NAICS codes but over 1000 observations are identified and their NAICS codes are added manually. Issuers with missing NAICS codes and less than 1000 observations are dropped, as they only represent a very small fraction of data points. The market share of each credit rating agency is calculated as the fraction of bonds ratings published by the particular firm in a specific industry and year. Following Becker and Milbourn (2011), two-digit NAICS codes are used to categorize the bond ratings by industry. The annual mean for Fitch market share and an overview of the industries is provided in Appendix 2.

Ratings by Duff & Phelps, a rating agency acquired by Fitch in 2000, are dropped in accordance with Becker and Milbourn (2011). Furthermore, there are a number of observations that are associated with a specific rating agency, date, and firm, that have the rating “Not Rated”. The agencies have slightly different definitions of this term, but it generally means that the bond is not currently rated or is no longer rated by the rating agency (S&P Global, 2019, Fitch Ratings, 2020). These are included when calculating market shares.[4] Given that we are interested in the number of bond ratings rather than the value of the rating, it does not have an impact that the rating is not on the AAA to D scale.

For the replication section of this paper, Fitch market share is the independent variable. We extend this to include a further measure of competition, the HH-Index. The reason for this is discussed further below. We chose to divide the value of the index by 10,000, which allows the index to fluctuate between 0 and 1, leading to more easily interpreted regression coefficients. Our HH-Index, based on the number of rated bonds per year, is also calculated using only the three biggest agencies market shares and not all NRSROs due to data limitations. However, since these three accounts for over 90% of all outstanding credit ratings (U.S. Securities and Exchange Commission, 2020), the effects of the market share of the other seven would not affect the calculations of the HH-Index significantly. The mean HH-Index for each industry is shown in Appendix 2. As Becker and Milbourn (2011) state in their paper, share of revenue would in theory be a better indicator of market share and the state of competition between the rating agencies. This information is however not readily available for the three rating agencies as they are private companies.

[4] Becker and Milbourn state that they use a data set of 1.1 million bond rating observations to calculate market share. Dropping “Not Rated” bonds results in a dataset that only contains 921,000 bonds for the years 1995-2006, which is why we assume that they include these. We also assume that they use multiple bond types to calculate market share (the data set includes ratings for corporate bonds and US treasury debt securities among others), since removing the non-corporate ratings also decreases the number of observations further.

4.1.2 Compustat

Compustat Capital IQ provides information on all of S&P's domestic long-term firm credit ratings, which are rated on a scale ranging from AAA to D, as well as the rating date, NAICS code, and a specific issuer ID.[5] See Appendix 1 for a thorough list of rating definitions. All firms with no rating or a rating of "N.M." are dropped, given that the value of the rating is of importance to the analysis.[6] Furthermore, only the last firm rating corresponding to the end of the firm's fiscal year is kept, as done by Bae et al. (2015). The ratings are then matched with their corresponding Fitch market share or HH-Index value through the two-digit NAICS codes and their year of rating.

We augmented this data further with annual accounting fundamentals from Compustat. The accounting data from the previous fiscal year is matched to the corresponding firm rating using the database firm ID, gvkey. We remove observations that do not list all accounting data and calculate a set of accounting ratios related to firm size, profitability, and indebtedness, that are used as firm controls for each specific firm.[7] For some firms, two sets of accounting data are available depending on which format they report in, either financial service (FS) or industrial format (INDL), with slightly different values. The majority of firms in the dataset report in INDL, so in order to attain the highest degree of comparability between companies, we use these values.

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[5] Our sample only includes firm credit rating data from S&P, due to data accessibility reasons. Becker and Milbourn (2011) also include data from Moody's in their dependent variable.

[6] "N.M." stands for "Not Meaningful" and is a descriptor for a category of rating outlooks. It does not exist on the rating scale for long-term credit ratings. Bonds with no rating and a rating of "N.M." accounted for approximately 1.7 million out of 2 million observations.

[7] Firm characteristics are the log of sales, log of book value of assets, cash divided by total assets (and its square), EBITDA (earnings before interest, taxes, depreciation, and amortization) divided by total assets (and its square), cash flow over total assets (and its square), EBITDA over sales (and its square), cash flow over sales (and its square), PPE (property, plant, and equipment) over total assets (and its square), interest expense over EBITDA (and its square), debt over total assets (and its square), all measured at the end of the previous fiscal year.

4.1.3 Variable Definitions

In Table 1 below, a definition of all variables used in the analysis is presented as well as the source, either Mergent FISD or Compustat. The dependent variables used in the regressions are shown in grey.

Table 1

This table includes a definition of all variables used in regressions as well as their source and name in the database. The dependent variables are shown in the grey boxes.

Variable name	Definition	Source
Firm credit rating	S&P Domestic Long-Term Issuer Credit Rating, translated into a numerical scale as in Appendix 1.	Compustat (splticrm)
Default within three years	A dummy variable for firms identified as defaulting (rating D or SD) within a three-year horizon.	Compustat (splticrm)
Fitch market share	Fraction of bonds rated by Fitch in a specific industry and year.	Mergent FISD (rating_type)
HH-Index	Sum of the squares of the market share of each competitor in an industry. (All calculated as for Fitch market share). Divided by 10,000.	Mergent FISD (rating_type)
Industry Fixed Effects	Dummies for industries. Industries refers to two-digit NAICS code. See Appendix 2 for an overview of industries.	Mergent FISD (naics_code) Compustat (naics)
Year fixed Effects	Dummies for years. 1995-2006 or 2010-2016, depending on which regression is performed.	Compustat (datadate)
Firm Fixed Effects	Dummies for firms. Firms are identified by their Global Company Key.	Compustat (gvkey)
Cluster_id	A variable created by grouping industries and years. Used in regressions to cluster by industry-year	
Log of sales	Log of (Sales/Turnover (Net))	Compustat (sale)
Log of book value of assets	Log of (Assets - Total)	Compustat (at)
Cash divided by total assets (and its square)	Cash divided by Assets - Total	Compustat (ch/at)
EBITDA divided by total assets (and its square)	EBITDA divided by Assets - Total	Compustat (ebitda/at)
Cash flow over total assets (and its square)	(Income before Extraordinary Items (Cash Flow) + Depreciation and Amortization) divided by Assets – Total	Compustat (ibc+dp)/at)
EBITDA over sales (and its square)	EBITDA over sales	Compustat (ebitda/sale)
Cash flow over sales (and its square)	(Income before Extraordinary Items (Cash Flow) + Depreciation and Amortization) divided by sales	Compustat ((ibc+dp)/sale)
PPE (Property, Plant, and Equipment) over total assets (and its square)	Property, Plant and Equipment - Total (Net) divided by Assets – Total	Compustat (ppent/at)
Interest expense over EBITDA (and its square)	Interest and Related Expense - Total divided by EBITDA	Compustat (xint/ebitda)
Debt over total assets (and its square)	(Long-Term Debt + Debt in Current Liabilities) divided by Assets - Total	Compustat ((dltt+dlc)/at)
Investment grade dummy	A dummy variable that takes the value one if firm credit rating is equal or higher than BBB- and zero otherwise.	Compustat (splticrm)

4.1.4 Data Distortion 2010-2016

Our extension investigates the time span 2010 to 2016. We choose our starting year as the financial crisis was deemed to have ended in 2009 and because the Dodd-Frank Act was passed in 2010 (The National Bureau of Economic Research, 2010, Dimitrov et al. 2015). Complete yearly data for S&P firm ratings from Compustat is only available until 2016, hence the end date of our time period. There are differences between the data set for 1995-2006 and this extended data set that require adaptations to Becker and Milbourn's (2011) methodology, even though we use the same data source. The distribution of ratings between the different rating agencies develops consistently over time, with Fitch accumulating an increasing number of yearly bond ratings through their expansionary growth and acquisition strategy in 1995-2006 (Becker and Milbourn, 2011). However, according to the Annual Report on NRSROs, the number of outstanding credit ratings for Fitch has been relatively stable 2010-2016, which indicates that their market share based on fraction of bond ratings should be stable as well. We observe specific anomalies to this pattern, specifically in the years 2014, 2015, and 2016, where our data shows that Fitch increased the number of bond ratings from approximately 70,000 in 2013 to 102,000 in 2014. The number of bond ratings increased further from 119,000 in 2015 to 211,000 in 2016, before dropping down to 51,000 in 2017.[8] This can be compared to S&P and Moody's 30,000-50,000 bond ratings per year. It also stands in contrast to the 2016 Annual Report on NRSROs, which shows that Fitch has a 13.0% market share in 2016 in terms of outstanding ratings, something that would presumably also be reflected in the number of ratings produced per year, even when historic bond rating differences are accounted for (U.S. Securities and Exchange Commission, 2016). Additionally, the Securities Industry and Financial Markets Association (2020) reported that the size of the outstanding bond market grew at a steady pace and there were no significant large jumps or changes in size in 2014, 2015 or 2016 that would justify such a large increase in rated notes related to new issuances. Since the number of bond ratings reported by Mergent FISD for Fitch no longer seem to be a good representation of the actual market share that the firm holds in the different industries, it needs to be amended to be utilized.

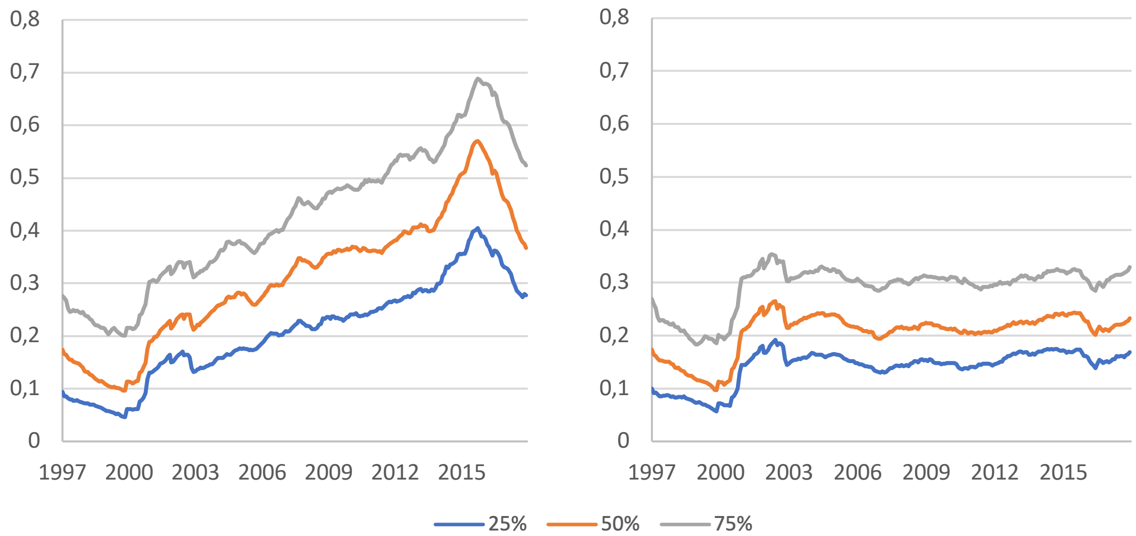
We find and deem that bond affirmations are the factor causing the data distortions. Affirmations are public statements by a rating agency that the current credit rating assigned to an issuer or debt obligation, which is not currently under review, continues to be appropriately positioned (Moody's Investor Services, 2020). Although this is a form of bond rating, the quantity of these that are conducted by Fitch spike considerably to be approximately 77,000 (76% of their ratings), 96,000 (80%), and 183,000 (87 %) in 2014, 2015, and 2016 respectively, compared to 20,000 (39%) in 2017. Since this pattern is not visible in the other rating agencies, this indicates that affirmations were not treated the same in these years. They are therefore dropped from the data set, leading to market share calculations that are more similar to the ones reported in the Annual Reports on NRSROs. The market shares calculated for Fitch based on this data can be seen in Figure 2, which are shown both including and excluding affirmations. We believe that this method of data cleaning provides a less noisy and more accurate reflection of Fitch market share.[9]

[8] Many of the bonds are rated a higher number of times per year than average, and some are even rated repeatedly every few days. The average rating of these specific issues did not change during this time period.

[9] Other parameters for data cleaning were also investigated, particularly bond types. No logical group of bond types to categorically mitigate the issue could be identified since the bulk of bonds with a drastically increased number of observations in the years 2014-2016 were varying types of corporate bonds, which were of interest to our study. We also contacted both the database provider Mergent FISD and Fitch Ratings, who did not have any comments on these anomalies.

Figure 2

Evolution of Fitch's market share by industry and month shown as 24-month rolling averages for the 25th, 50th, and 75th percentile industries. Fitch's market share is computed by dividing the number of bond ratings assigned by Fitch by the sum of the number of bond ratings assigned by S&P, Moody's and Fitch. In the first graph, bond affirmations are included in the calculation of market share. In the second graph, bond affirmations are excluded in the calculation of market share.



Becker and Milbourn (2011) exploit that Fitch's market share varies across industries to complete their empirical analysis, as they take advantage of cross-industry variation to test the effects of competition on rating quality. Although there is still variation across industries, the market share of Fitch does not vary as much over 2010-2016 as it does over 1995-2006, with the standard deviation of the variable dropping from 0.108 to 0.063 (after adjusting for affirmation ratings). At this point, Fitch has reached a more stable within-industry market share and become an established actor, as can be seen from Figure 2. To account for this possible problem with Fitch market share as a measure of competition, as well as possible significant changes in the relative market shares of the incumbent firms, the HH-Index is added to verify the validity of our findings.

4.2 Descriptive Statistics

In Table 2, we present our descriptive statistics. Compared to Becker and Milbourn (2011), our average firm credit rating for the period 1995-2006 is lower by 0.407 (2.25%) and the standard deviation higher by 0.308 (7.84%). Our number of observations is also higher by 713. For market share, the number of observations represent the number of industry-year cells (24 industries and 12 years of data). The average Fitch market share in our data set is 0.008 higher (3.77%), with a standard deviation that is 0.025 (17.61%) lower. The mean of default within three years is 0.014 higher than the 0.010 found by Becker and Milbourn (2011), while the number of observations is lower by 102. This provides evidence that we have not been able to identify every step they have taken when cleaning the data, but still have created a similar data set.

2010-2016 only considers seven years of data, leading to overall fewer observations. Between the two time periods of interest firm credit ratings decreased by 0.255, with the average rating dropping from being closest to a BBB- rating to a BB+ rating. The decrease in standard deviation is more substantial. Fitch market share increases dramatically from 1995-2006 to 2010-2016 when all bond ratings are considered in the calculation, to an average of 0.449. However, the variable used in the analysis drops all affirmed rating observations, resulting in a more stable market share with a mean of 0.229 over time with a lower spread.

Table 2
Each column present descriptive statistics for the variables of interests. Number of observations for Fitch market share and HH-Index refers to the number of industry-year cells and is based on 24 industries.

Descriptive Statistics

1995–2006	Firm Credit Rating	Fitch Market Share (All Bonds)	Fitch Market Share (Removing Affirmations)	HH-Index (All Bonds)	HH-Index (Removing Affirmations)	Default within three years (1995–2005)
Mean	17.685	0.220	0.199	0.383	0.385	0.024
Median	18	0.220	0.189	0.365	0.373	0
Standard Deviation	4.238	0.117	0.108	0.062	0.050	0.154
Number of Observations	20,343	288	288	288	287	18,549
2010–2016						(2010–2015)
Mean	17.430	0.449	0.229	0.396	0.368	0.008
Median	18	0.447	0.226	0.370	0.359	0
Standard Deviation	3.555	0.147	0.063	0.070	0.033	0.090
Number of Observations	11,174	168	168	168	168	9,649

4.3 Methodology

Our paper examines two dimensions of rating quality, risk classification (through rating level) and rating informativeness, which together provide a comprehensive understanding of how rating quality has been affected by competition over time, both before and after the financial crisis. Quality can be perceived differently depending on who uses the rating. We follow the reasoning of Becker and Milbourn (2011), who argue that the risk classification of a rating should be stable, in that each grade has a steady meaning over time, to be easily interpretable and understood by investors. Shifts along the rating scale leading to higher average ratings are deemed to be negative as the least sophisticated investors might not be able to fully incorporate information on the variation of the rating scale over time. As stated by Becker and Milbourn (2011), an increase in rating level is a direct consequence of competition, if competition leads to rating levels also reflecting issuer preferences for higher ratings instead of solely credit quality. A rating performs well in terms of credit informativeness if it can predict future default and group firms based on their credit risk, regardless of the level of competition between rating agencies. Default rate is therefore one of the most direct ways to examine how competition impacts rating informativeness.

4.3.1 Statistical Method

To answer the research question of how the rating quality of firm ratings issued by S&P has been affected by competition, we perform ordinary least squares (OLS) regressions and ordered probit regressions, in accordance with Becker and Milbourn (2011). Of interest is to identify whether a causal relationship exists between competition and rating quality. To empirically test this, we employ two sets of tests and include a number of control variables to rule out possible omitted variables bias.

4.3.1.1 Regressions on rating level

$$(1)\ R_{i,k} = \beta_0 + \beta_1 Competition_{i,j} + \varepsilon$$

Where:
$R_{i,k}$ = Firm long-term credit rating for a firm *k* in a specific year *i*
$Competition_{i,j}$ = Fitch's market share or HH-Index for a specific year *i* and industry *j*

We first perform a series of OLS regressions to empirically test how Fitch market share as well as HH-Index affects rating levels. Initially, the dependent variable, firm credit rating (converted to a numerical scale, see Appendix 1), is regressed only on the independent variable, Fitch market share or HH-Index, without the inclusion of controls. This is illustrated in Equation 1. Each observation represents a firm-year. As this is not enough to conclude that a causal relationship exists between these two variables, in the subsequent regressions, different combinations of controls are added. Following Becker and Milbourn (2011), we first include industry and year fixed effects. Secondly, we include year and firm fixed effects as well as the 18 accounting measures as firm controls. The OLS regressions treat every step of the dependent variable firm credit rating as equal, which might not be representative of how firm ratings are assigned. Given that we cannot be certain if each grade of firm credit rating is equidistant from the adjacent grades, we also include an ordered probit regression, which allows the effects of firm credit rating to vary across the rating scale (Becker and Milbourn, 2011). Industry and year fixed effects are also included in this specification. Lastly, two robustness tests are included by collapsing data on mean and median, from firm-year level to industry-year level, which lowers the number of observations drastically. Industry-years with fewer than 25 individual firm ratings are excluded. Industry and year fixed effects as well as firm controls are included. These OLS regressions mitigate concerns about error correlation and that the same firm is repeatedly sampled while also removing within-cell variation (Becker and Milbourn, 2011). An overview of the model specifications for all OLS regressions is presented in Appendix 3.

The first set of regressions are conducted for both of our sample periods, 1995-2006 and 2010-2016. For 1995-2006, we run the regressions with data cleansed in two different ways. The first is a replication of Becker and Milbourn (2011), in order to verify that their methodology is correctly understood. The second cleaning method uses the adaptations that we found to be appropriate for the data in 2010-2016, namely dropping affirmation ratings, to verify that this method still produces results with similar effects. In accordance with Bae et al. (2015), we also run the regressions when isolating the later part of the time period, 2000-2006. Since Fitch growth was more prominent during that time, as indicated by Figure 1, the effects of competition on rating inflation should be more visible. We expect to identify the same effects as Becker and Milbourn (2011), both using Fitch market share and HH-Index for 1995-2006. Using data from 2010-2016, we test the hypothesis that increased competition leads to higher rating levels to determine if the correlation still persists in a later time period.

4.3.1.2 Regressions on rating informativeness

$$(2)\ D_{i,k} = \beta_0 + \beta_1 Competition_{i,j} + \beta_2 Rating_{i,k} + \beta_3 Competition_{i,j} * Rating_{i,k} + \varepsilon$$

Where:
$D_{i,k}$ = Dummy variable for a firm *k* in a specific year *i* defaulting within a three-year horizon
$Competition_{i,j}$ = Fitch's market share or HH-Index for a specific year *i* and industry *j*
$Rating_{i,k}$ = Investment grade dummy or firm long-term credit rating for a firm *k* in a specific year *i*

The second part of the analysis quantifies the relationship between competition and rating informativeness through a second set of OLS regressions. The dependent variable is "default within three years" which initially is regressed on the independent variables Fitch market share, an investment grade dummy, and an interaction between these. In the second regression, the investment grade dummy is replaced by the firm credit rating (the numerical rating value), as shown in Equation 2. No controls are included. Each observation is a firm-year in which the firm can be identified as defaulting or not defaulting within three years. To accurately establish if ratings predict default, we include industry and year fixed effects as well as firm controls in the third regression. Furthermore, since predicting default could potentially be harder in some industries and years, we include interactions between firm credit rating and fixed effects for industry and years in the fourth regression (Becker and Milbourn, 2011). Lastly, a robustness test is included, where data is collapsed to the mean values by industry-year cell. Industry and year fixed effects as well as firm controls are also included. Both Fitch market share and HH-Index are tested separately as independent variables. An overview of the model specification for all OLS regressions are presented in Appendix 3.

This set of regressions are conducted for the same sample periods as the rating level regressions. Once again, we expect our results to yield the same effects as those found by Becker and Milbourn (2011) in 1995-2006. For 2010-2016, we investigated the second hypothesis that increased competition between rating agencies leads to a decline in rating informativeness.

4.3.1.3 Controls

Industry and year fixed effects are included in the regressions, as years exhibit different macroeconomic trends and industries may have different average rating levels. The firm fixed effects and firm controls account for differences in size, cash flows, and financial health. The inclusion of these helps us determine if there is a causal relationship between competition and the behaviour of rating agencies, since the identified effect can only be considered valid if competition can be treated as exogenous in the regression models we study (Becker and Milbourn, 2011). Endogeneity exists if competition in a certain industry is correlated with other factors also affecting the dependent variable, which we try to mitigate through the inclusion of controls.

4.3.1.4 Robust standard errors

To account for correlated errors, the standard errors of our regressions are clustered around each industry-year, as our variables of interest, Fitch market share and HH-Index, vary at this level. For the regressions when data is already collapsed at industry-year level, heteroskedasticity-robust standard errors are also produced.

4.3.1.5 Checking for multicollinearity

Multicollinearity is also investigated as a potential issue, to establish if any of the independent variables we study are highly correlated. High levels of correlation could lead to less precision in our coefficient estimates and is therefore primarily verified through the variance inflation factor (VIF). For regressions where VIF is not applicable, a correlation matrix is used to identify potential multicollinearity. As we are only interested in how our independent variables, Fitch market share and HH-Index, affect firm credit ratings, we focus on mitigating a possible multicollinearity issue only for these independent variables, and not the control variables. To our knowledge, multicollinearity in the control variables will not affect our estimate for the market share or HH-Index variable.

5. Results

5.1 Rating Level

5.1.1 Replication 1995-2006

The first test is a replication of one of Becker and Milbourn's (2011) main findings. Following them, we regress firm credit rating on Fitch market share and include a number of control variables. Our results are presented in Table 3. These results show that when Fitch market share (i.e. competition) increases, firm ratings issued by S&P becomes more favourable for issuers in that they generally lie higher on the rating scale. This decreases the firm's cost of debt since higher rated firms are deemed to be safer and investors do not require as high of a return on their investments (Kisgen, 2006). In the first regression in Column 1, when no controls are included, the effect of the positive correlation between firm rating and Fitch market share is larger than in subsequent tests. This test might however be unreliable since no controls are included and omitted variable bias could be present. In Column 2 and 3 different sets of fixed effects and controls are included in the regressions. While the positive correlation still exists between Fitch market share and firm ratings, the effect is modest. For a single standard deviation change in Fitch market share (0.117), average firm rating is expected to increase by 0.17 when year and industry dummies are included and by 0.12 when year dummies, firm dummies, and firm controls are included. In terms of the rating scale, this is approximately equivalent to a one step upgrade (e.g. from A- to A) for one out of every fifth firm and one out of every tenth firm. In Column 4 an ordered probit model is used instead of an OLS. The results using this specification do not alter the conclusion that Fitch market share is positively correlated with S&P firm credit rating. Collapsing data on mean yields a positive significant estimate for Fitch market share, with a lower magnitude compared to Column 2 (average firm rating is expected to increase by 0.1 for a one standard deviation change). The estimate for Fitch market share when data is collapsed by median is positive and insignificant. The coefficient was also found to be insignificant by Bae et al. (2015).

Generally, the results are similar to those of Becker and Milbourn (2011). Their results are shown in grey in Table 3. In some instances, the significance level is different, although still significant. The overall effects, including the direction of the coefficients, R-square value, and significance level, are close to those found by Becker and Milbourn (2011). The tests where we solely examine the later part of the time period, 2000-2006, interestingly yield results that show an insignificant correlation between competition and rating level. These tests are presented in Appendix 4.

Dropping affirmation ratings from the data set when calculating Fitch market share results in significant positive coefficients in four tests, compared to five when affirmations are not removed. The estimated coefficient from the ordered probit specification is now insignificant. In the other regressions, the significance levels as well as the effects of Fitch market share on firm credit ratings differ slightly. For a one standard deviation change in Fitch market share (0.108), average firm credit rating is instead expected to increase by 0.12 when year and industry dummies are included and 0.11 when year dummies, firm fixed effects, and firm controls are included. Results of these regressions are presented in Appendix 5. Although there are deviations from Table 3, the overarching conclusion that more competition leads to higher rating levels still holds.

Table 3
In the table below, firm credit rating (S&P Domestic Long-Term Issuer Credit Rating) is regressed on Fitch market share or HH-Index. The dependent variable, firm credit rating, is based on a numerical scale, ranging from 1 (D) to 28 (AAA). Fitch market share is the fraction of bonds rated by Fitch in an industry-year cell. HH-Index is the sum of the squares of the market share of each rating agency in an industry-year cell, divided by 10,000. Firm controls include 18 firm-specific accounting measures. Industries refers to two-digit NAICS codes. In Column 5 and 6 data is collapsed, using mean and median, on industry-year level. Standard errors are clustered at industry-year level, except in Column 5 and 6. All standard errors are heteroskedasticity-robust and shown in parentheses. Intercepts are not reported. Significance level is reported as *** representing 1%, ** 5%, * 10%. Becker and Milbourn (2011) results are shown in grey.

Replication 1995-2006	Dependent variable: firm credit rating					
	OLS (1)	OLS (2)	OLS (3)	Ordered Probit (4)	OLS average by cell (5)	OLS median by cell (6)
Fitch Market Share	2.874**	1.461**	0.984**	0.349*	0.825*	0.475
	2.395**	1.325**	0.784*	0.3615**	1.533***	1.754**
	(1.309)	(0.731)	(0.441)	(0.184)	(0.47)	(0.875)
	(1.123)	(0.566)	(0.432)	(0.156)	(0.570)	(0.846)
Year Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	Yes	No	Yes	Yes	Yes
Firm Fixed Effects	No	No	Yes	No	No	No
Firm Controls	No	No	Yes	No	Yes	Yes
R squared	0.005	0.139	0.881	n/a	0.965	0.934
	(0.004)	(0.141)	(0.900)		(0.961)	(0,914)
Number of Observations	20,343	20,343	20,343	20,343	188	188
HH-Index 1995-2006						
HH-Index	-3.617	-2.771*	-0.141	-0.783**	-2.113**	-1.037
	(2.683)	(1.578)	(0.817)	(0.392)	(1.017)	(1.755)
Year Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	Yes	No	Yes	Yes	Yes
Firm Fixed Effects	No	No	Yes	No	No	No
Firm Controls	No	No	Yes	No	Yes	Yes
R squared	0.001	0.139	0.881	n/a	0.965	0.934
Number of Observations	20,343	20,343	20,343	20,343	188	188

Next, we use HH-Index instead of Fitch market share as the independent variable. Results are presented above in Table 3. Note that the coefficients are all negative. A negative correlation implies that when the HH-Index increases i.e. when the industry becomes more concentrated, the rating level is lower. More competitive industries therefore exhibit higher rating levels, which is consistent with the results found when Fitch market share is used. In terms of effect, for a one standard deviation change in HH-Index (0.062), average firm credit rating is expected to decrease by 0.17 when industry and year dummies are included. Generally, the magnitude of effects is similar or higher in comparison to Fitch market share but is weaker in terms of significance level, implying that HH-Index as a measure of competition is more noisy.

Regressing firm credit rating on HH-Index excluding bond affirmations yields similar results in terms of magnitude to when affirmations are included. When year and industry dummies are included, a one standard deviation increase in HH-Index (0.050) is expected to decrease average firm credit rating by 0.17. The results are presented in Appendix 5. The correlations are also more significant than those including affirmations.

5.1.2 Extension 2010-2016

Becker and Milbourn (2011) establish that competition between rating agencies lead to increased rating levels, while Dimitrov et al. (2015) finds that higher levels of consolidation displayed lower rating levels after the passing of Dodd-Frank Act. We now build on this research to study what effects are present across the entire time period 2010-2016. The results are shown in Table 4. In Column 1 the estimated coefficient for Fitch market share is highly significant and the effect is almost twice as large as in the time span 1995-2006, implying that the positive correlation between our measure of competition and rating level still exists. Given that no controls are included in this regression, we may be overestimating the effects of market share as an explanatory variable. In subsequent regressions, when the fixed effects and controls are included none of the estimated coefficients are significant, which shows that the changes in rating level can be explained through variation across industries, years, and firms. Our descriptive statistics in Table 2 show that average firm rating levels had dropped slightly from earlier years, which is in line with the findings of Dimitrov et al. (2015), who suggest that the drop in ratings stems from the passing of the Dodd-Frank Act. However, the general decrease in rating level alone does not provide evidence that industry-years are affected differently based on competition. Collapsing data by industry-year level, as in Column 5 and 6, leads to negative and significant regression coefficient, implying that competition seems to lead to lower rating levels. In these tests all within-industry variation is eliminated and all industries are equally weighted. Some sectors, such as information, manufacturing of metals and machinery, and finance & insurance are overrepresented in our firm rating sample while construction, wholesale trade, and retail trade are underrepresented. As an example, the finance & insurance sector has 7.92 times more firm ratings than the construction industry. Weighting them equally diminishes the impact of the overrepresented industries and vice versa for the underrepresented ones. This is the most likely source of the reversed sign of the correlation. When the HH-Index is used as the independent variable for the period 2010-2016, the results are almost conclusively insignificant, as seen in Table 4. This in combination with the results using Fitch market share provide evidence that competition no longer is a cause of rating level differences.

Table 4

In the table below, firm credit rating (S&P Domestic Long-Term Issuer Credit Rating) is regressed on Fitch market share or HH-Index. The dependent variable, firm credit rating, is based on a numerical scale, ranging from 1 (D) to 28 (AAA). Fitch market share is the fraction of bonds rated by Fitch in an industry-year cell. HH-Index is the sum of the squares of the market share of each rating agency in an industry-year cell, divided by 10,000. Affirmations are removed as bond ratings. Firm controls include 18 firm-specific accounting measures. Industries refers to two-digit NAICS codes. In Column 5 and 6 data is collapsed, using mean and median, on industry-year level. Standard errors are clustered at industry-year level, except in Column 5 and 6. All standard errors are heteroskedasticity-robust and shown in parentheses. Intercepts are not reported. Significance level is reported as *** representing 1%, ** 5%, * 10%.

Fitch Market Share 2010-2016	Dependent variable: firm credit rating					
	OLS (1)	OLS (2)	OLS (3)	Ordered Probit (4)	OLS average by cell (5)	OLS median by cell (6)
Fitch Market Share	10.011***	1.197	0.010	0.317	-1.486**	-3.414**
	(3.321)	(0.808)	(0.575)	(0.240)	(0.590)	(1.658)
Year Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	Yes	No	Yes	Yes	Yes
Firm Fixed Effects	No	No	Yes	No	No	No
Firm Controls	No	No	Yes	No	Yes	Yes
R squared	0.014	0.164	0.941	n/a	0.989	0.956
Number of Observations	11,174	11,174	11,174	11,174	108	108
HH-Index 2010-2016						
HH-Index	-16.150	-0.892	-0.451	-0.214	2.734***	5.191
	(13.175)	(1.696)	(1.045)	(0.491)	(0.990)	(3.391)
Year Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	Yes	No	Yes	Yes	Yes
Firm Fixed Effects	No	No	Yes	No	No	No
Firm Controls	No	No	Yes	No	Yes	Yes
R squared	0.008	0.164	0.941	n/a	0.989	0.955
Number of Observations	11,174	11,174	11,174	11,174	108	108

Overall, we are able to replicate Becker and Milbourn's (2011) main test, showing that increased competition measured as Fitch market share leads to higher rating levels in 1995-2006. The correlations are still present when bond affirmations are dropped and the same is true when HH-Index is used (although some regressions do not yield as significant results as we find in the replication tests). Regressions on data from 2010-2016 do not lead to significant correlations, regardless of the measure of competition used, implying that competition between credit rating agencies no longer is a driver of higher rating levels.

5.2 Rating Informativeness

Examining rating level on its own is not enough to decisively dispute that competition no longer affects rating quality. It is entirely possible that rating informativeness could be systematically affected by competition between rating agencies, even though rating level has not exhibited a correlation with competition in 2010-2016.

5.2.1 Replication 1995-2005

We use the data from 1995-2005 to replicate the regressions of Becker and Milbourn (2011).[10] In Table 5 Column 1, we first regress default within three years on an investment grade dummy, Fitch market share, and an interaction term between these two. As expected, being rated investment grade has a large and highly significant negative impact on the rate of default of the firm. The coefficient of the interaction term is significant and positive, implying that the difference in rate of default between investment grade and speculative grade firms falls as competition between rating agencies in an industry-year increase. This indicates that rating informativeness falls, as it is more communicative to users of the rating if there is a substantial difference in default rates at different rating levels. Most importantly, the informational content of ratings should be independent of competition. Speculative grade firms are 5.74 times more likely to default than firms with an investment grade rating in industries where competition is high (75%, 0.290), 7.97 times more likely to default than investment grade firms when competition is median (50%, 0.226), and 11.60 times more likely to default than investment grade firms when competition is low (25%, 0.154). Our identified effects are larger than those found by Becker and Milbourn (2011), in terms of both absolute magnitude and in spread, and are closer to those of Bae et al. (2015).

In Column 2, the investment grade dummy is replaced by the numerical value of the firm credit rating itself. This version still examines the linear relationship between rating and default but captures more detailed variation in firm ratings. All coefficients are still significant. Although the credit rating term is negative and significant, it only has a marginal effect on default rate relative to the interaction term, since the magnitude of the interaction term is larger and positive. This means that as Fitch market share increases, the negative impact of credit rating level on default rate decreases. We compare the implications of this regression for the most common investment grade rating in our sample, BBB, and the most common speculative grade rating, B+. Firms with a B+ rating are 3.42 times more likely to default than firms with a BBB rating in industries where competition is high (75%, 0.290), 3.60 times more likely to default than a BBB-rated firm when competition is median (50%, 0.226), and 3.78 times more likely to default than a BBB-rated firm when competition is low (25%, 0.154). The effects are still between 55-125% larger in magnitude than those found by Becker and Milbourn (2011), but are much closer in absolute terms than the regression results using the investment grade dummy.

In Column 3 we find that the magnitude of our findings decreases further when controlling for industry and year fixed effects as well as including firm controls.[11] In Column 4 interaction

[10] The binary dependant variable, default within a three year time horizon, cannot contain non-zero values in the last year of observations (2006 in the earlier data set and 2016 in the later one) and are therefore dropped in all tests concerning rating informativeness.

[11] Initially the software used could not estimate a F-value for the model. We find the reason to be an outlier in the squared cash flow over sales-variable, where the firm Seven Seas Petroleum Inc. had an extreme value in 1999. The model is estimated properly when this observation is removed, and has almost no impact on the estimated coefficients. To check the robustness we also try excluding the variable as a whole as well as winsorize the firm

terms between firm credit ratings and all year and industries are added. We find that all coefficients are insignificant, which is also what Bae et al. (2015) find. Given that the inclusion of the additional interaction terms leans very hard on the data, we conclude that this test is highly dependent on the sample.

Collapsing the data at industry-year level and regressing the fraction of firms defaulting per industry-year on firm credit rating, market share, and an interaction term between the two, results in non-significant coefficients for all independent variables. This indicates that even when only plotting the percentage of defaults per industry-year cell, and therefore controlling for the differences in number of observations per industry-year cell, competition does not affect default rates. Our findings are shown in Column 5 and are in line with those of Bae et al. (2015), even as Becker and Milbourn (2011) identify coefficients significant at the 1% level. Of note is that our sample includes a larger number of industry-year cells than the 189 that Becker and Milbourn (2011) use.

When dropping affirmations from our sample, we find that only the variable measuring rating level, either the investment grade dummy or the firm credit rating, is significant. Different degrees of competition between rating agencies in an industry therefore have no significant impact on default rates. These results can be seen in Appendix 6. The results of the regression in Column 4, where further interaction terms are added, and 5, where data is collapsed, are both insignificant, which is in line with our findings when using the entire data set of bonds in market share calculations. The results of these regressions indicate that our replicated default results are sensitive to the inclusion of affirmations, but are still a necessary adjustment to avoid data distortion in our sample 2010-2016.

The results of our regressions using HH-Index are shown in Table 5. Only the coefficient for the HH-Index and the interaction term are significant, which contrasts the results when Fitch market share is used, since all three explanatory coefficients are significant in those tests. The positive effect of a change in credit rating level on default rate is larger in the regressions using HH-Index than those using Fitch market share, since the magnitude of the interaction term is approximately twice as large. The credit rating term can be expected to be insignificant as there are no data points for which HH-Index is zero, which makes the effect of solely credit rating difficult to estimate. The likeliness of default is overall larger than that found when using Fitch market share, and the effect size decreases when fixed effects are included. Neither adding the additional interaction terms nor collapsing data to an industry-year level produces significant results.

When excluding bond affirmations to calculate HH-Index, we once again observe the sensitivity of the results to affirmation observations. Relative to when all bonds are included, the regressions using firm credit rating as opposed to investment grade dummy display slightly different levels of significance and a smaller effect size, meaning that the difference in default rate is less pronounced between higher and lower levels of competition. Using the investment grade dummy does not lead to significant results. The results of these regressions can be found in Appendix 6.

The general trends indicate that, during the years 1995-2005, higher levels of competition between rating agencies in an industry lead to both higher and less informative S&P firm credit

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controls at the 1th and 99th percentile to account for other potential outliers. However, the effects and significance-level largely remains the same in both these cases. This is done for all subsequent regressions 1995-2006 including firm controls, which does not change the implication of effects.

ratings. HH-Index generally exhibits the same correlations that Fitch market share does. However, the variable for firm credit rating is insignificant in these tests. Dropping affirmations also leads to slight variations in results. It does not seem to perfectly capture the correlations found using the full data set from 1995-2005, however, it does not lead to completely uncorrelated results. As explained, our results deviate slightly from Becker and Milbourn (2011). We believe this is due to the inclusion of several interaction terms in the regressions, which lean harder on the data.

Table 5

In the table below, coefficient estimates are shown from five OLS-regressions. The dependent variable is a dummy variable for firm default (one if a firm is defaulted within the subsequent three years, zero otherwise) which is regressed on Fitch market share (or HH-Index), a credit rating term, and the interaction of Fitch market share (or HH-Index) with the credit rating term. Control variables include industry and year fixed effects, 18 firm-specific accounting measures, as well as interactions between credit rating and year/industry fixed effects. Industries refers to two-digit NAICS codes. In Column 5 data is collapsed, using mean, at industry-year level. Standard errors are clustered at industry-year level, except in Column 5. All standard errors are heteroskedasticity-robust and shown in parentheses. Intercepts are not reported. Significance level is reported as *** representing 1%, ** 5%, and * 10%. Becker and Milbourn's (2011) results are shown in the grey.

Replication default tests using Fitch market share 1995-2005	Dependent: Default within three years				
	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS, averaged by industry-year (5)
IG-dummy*Fitch market share	0.132*** 0.089***				
	(0.045) (0.030)				
IG dummy	-0.069*** -0.033***				
	(0.011) (0.067)				
Credit rating*Fitch market share		0.018** 0.0123***	0.014** 0.0123***	0.012 0.0063*	0.003 0.0070***
		(0.007) (0.070)	(0.006) (0.001)	(0.008) (0.0038)	(0.009) (0.001)
Credit rating		-0.011*** -0.0045***	-0.013*** -0.0049***	-0.009	-0.001 -0.0094**
		(0.002) (0.0009)	(0.002) (0.0011)	(0.005)	(0.006) (0.004)
Fitch market share	-0.118*** -0.080***	-0.360*** -0.253***	-0.253** -0.229***	-0.210 -0.116	-0.077 -0.121***
	(0.042) (0.028)	(0.138) (1.250)	(0.117) (0.085)	(0.163) (0.080)	(0.178) (0.023)
Year Fixed Effects	No	No	Yes	Yes	Yes
Industry Fixed Effects	No	No	Yes	Yes	Yes
Year Fixed Effects*Credit rating	No	No	No	Yes	No
Industry Fixed Effects*Credit rating	No	No	No	Yes	No
Firm Controls	No	No	Yes	No	Yes
R-squared	0.019 0.008	0.046 0.001	0.074 0.024	0.081 0.024	0.563 0.571
Number of Observations	18,549	18,549	18,548	18,549	242

Default tests using HH-Index 1995-2005					
IG-dummy*HH-Index	-0.250**				
	(0.118)				
IG dummy	0.053				
	(0.044)				
Credit rating*HH-Index		-0.041**	-0.037**	-0.022	-0.018
		(0.019)	(0.018)	(0.023)	(0.018)
Credit rating		0.008	0.003	0.002	0.007
		(0.007)	(0.007)	(0.010)	(0.011)
HH-Index	0.262**	0.853**	0.691**	0.455	0.379
	(0.116)	(0.381)	(0.346)	(0.462)	(0.408)
Year Fixed Effects	No	No	Yes	Yes	Yes
Industry Fixed Effects	No	No	Yes	Yes	Yes
Year Fixed Effects*Credit rating	No	No	No	Yes	No
Industry Fixed Effects*Credit rating	No	No	No	Yes	No
Firm Controls	No	No	Yes	No	Yes
R-squared	0.019	0.046	0.074	0.081	0.566
Number of Observations	18,549	18,549	18,548	18,549	242

5.2.2 Extension 2010-2015

We examine the ability of competition to predict default at the three-year horizon using the data set from 2010-2015. There is no longer a significant positive correlation between competition and rating level in these years, but it is still of interest to examine whether rating informativeness could be affected by competition between rating agencies. However, there is a low number of "default within three years" observations in these years compared to the data from the earlier years, only 78 compared to 452, implying that the power of these tests is limited. In the data sample, none of the 78 firm-year observations where a firm is identified as defaulting within three years comes from firms who were rated investment grade. The implication of this is that the model specification in which default within three years is regressed on an investment grade dummy, Fitch market share, and an interaction term between these two cannot be estimated properly and is therefore excluded in the analysis for this time period.

The results of the OLS regressions using Fitch market share are presented in Table 6. The first regression indicates that there is still a significant relationship between competition and default rate. However, these correlations become insignificant once firm controls and fixed effects are accounted for. This differs from the time period 1995-2005, where firm credit ratings together with firm accounting data are better at predicting default than ratings alone. Credit rating level is still a significant explanatory variable, but to a lesser degree, and the effect size is smaller. Furthermore, in Column 3, when interactions of firm credit ratings and both industry and year fixed effects are included, none of the coefficients are statistically significant. When including these interactions, there are over 50 coefficients to be estimated from a dataset with less than 100 defaults, implying that this specification is not a good fit for the data set. The results of the regressions using HH-Index are also presented in Table 6. All regressions lead to insignificant results, implying that the information content of ratings is not diminished by varying the level of competition between credit rating agencies.

Overall, our results for 2010-2015 are mixed, with some tests indicating a significant negative correlation between firm credit rating and default rate. This is expected and positive in terms of rating informativeness, given that it is desirable for higher rated firms to default at a lower rate. Although Fitch market share and the interaction term initially shows a significant correlation with the dependent variable, these effects disappear when firm accounting controls are added, and industry and year fixed effects are accounted for. Regressions using HH-Index lead to conclusively insignificant correlations for all independent variables. While our results do not explain what the actual cause of rating informativeness is, they show that Fitch market share and HH-Index are not drivers of lower rating quality. In the time period examined by Becker and Milbourn (2011), competition has a significant effect on default rates, which we do not identify for this period. Rating informativeness has therefore, in relation to competition, generally improved from the time period 1995-2005 to 2010-2015.

Table 6

In the table below, coefficient estimates are shown from four OLS-regressions. The dependent variable is a dummy variable for firm default (one if a firm is defaulted within the subsequent three years, zero otherwise) which is regressed on Fitch market share (or HH-Index), a credit rating term, and the interaction of Fitch market share (or HH-Index) with the credit rating term. Control variables include industry and year fixed effects, 18 firm-specific accounting measures, as well as interactions between credit rating and year/industry fixed effects. Bond affirmations are excluded from market share calculations. Industries refers to two-digit NAICS codes. In Column 4 data is collapsed, using mean, at industry-year level. Standard errors are clustered at industry-year level, except in Column 4. All standard errors are heteroskedasticity-robust and shown in parentheses. Intercepts are not reported. Significance level is reported as *** representing 1%, ** 5%, and * 10%.

Default tests using Fitch market share 2010-2015			Dependent: Default within three years	
	OLS	OLS	OLS	OLS, averaged by industry-year
	(1)	(2)	(3)	(4)
Credit rating*Fitch market share	0.028*	0.018	-0.003	0.011
	(0.016)	(0.016)	(0.014)	(0.008)
Credit rating	-0.010**	-0.008**	-0.001	-0.002
	(0.004)	(0.004)	(0.003)	(0.004)
Fitch market share	-0.559*	-0.317	0.019	-0.197
	(0.304)	(0.287)	(0.260)	(0.149)
Year Fixed Effects	No	Yes	Yes	Yes
Industry Fixed Effects	No	Yes	Yes	Yes
Year Fixed Effects*Credit rating	No	No	Yes	No
Industry Fixed Effects*Credit rating	No	No	Yes	No
Firm Controls	No	Yes	No	Yes
R-squared	0.025	0.049	0.080	0.628
Number of Observations	9,649	9,649	9,649	132
Default tests using HH-Index 2010-2015				
Credit rating*HH-Index	-0.054	-0.043	0.032	-0.024
	(0.036)	(0.037)	(0.032)	(0.019)
Credit rating	0.016	0.011	-0.013	0.009
	(0.013)	(0.013)	(0.012)	(0.007)
HH-Index	1.061	0.722	-0.581	0.419
	(0.696)	(0.718)	(0.625)	(0.337)
Year Fixed Effects	No	Yes	Yes	Yes
Industry Fixed Effects	No	Yes	Yes	Yes
Year Fixed Effects*Credit rating	No	No	Yes	No
Industry Fixed Effects*Credit rating	No	No	Yes	No
Firm Controls	No	Yes	No	Yes
R-squared	0.023	0.049	0.080	0.627
Number of Observations	9,649	9,649	9,649	132

5.3 Multicollinearity

We find moderate multicollinearity in our data. The average VIF for the rating level regressions 1995-2006 is 4.17 for the Fitch market share variable and 3.45 for HH-Index. For 2010-2016 the average VIF is 2.71 for Fitch market share and 1.93 for HH-Index. Correlation in the regressions is also examined through correlation matrices, which show that correlations between our variable of interest and control variables are generally below 0.5 or above -0.5. Based on these results, we decide not to take any corrective measures. Between control variables, such as between industries dummies or firm controls, high correlation is present in some regressions. To our knowledge, multicollinearity in control variables will not affect our estimates for Fitch market share and HH-Index, as long as they are not correlated with each other. We find that dropping highly correlated explanatory variables does not change the identified effects. Part of the correlations between the firm controls are also explained by the inclusion of squared accounting terms. For the default tests in which interaction terms are included, correlation between variables is a by-product of the model specifications.

6. Discussion of Findings

Fitch entering the corporate rating market as a new entrant led to a drop in rating quality, where a higher market share displayed a positive correlation with rating level (Becker and Milbourn, 2011). We confirm these results to find that firm rating levels published by the incumbent rating agency S&P increase in the industries where Fitch rates a larger portion of bonds in the years 1995-2006. Rating informativeness also deteriorates, shown through the difference in default rates between investment grade and speculative grade firm ratings decreasing. This can be attributed to a reputational mechanism where future revenue influences current rating decisions. The entrance of a new market player decreases future expected revenue, which decreases the incentive to provide high quality ratings as an investment in reputation, and instead shifts focus to short-term profits (Becker and Milbourn, 2011).

Our results for 2010-2016 show no significant correlation between competition and rating quality. Therefore, we find no evidence that our hypotheses, that increased competition leads to both higher rating level and declined informativeness, are true for this time period. Fitch's market share is stable over time in most industries throughout the period, and no large structural shocks have been identified after the passing of Dodd-Frank. Interestingly, we find that the correlation that Becker and Milbourn (2011) identify is largely insignificant when only the years 2000-2006 are considered, which is also what Bae et al. (2015) find. This shows that competition between rating agencies within an industry had already ceased to be a driver of rating quality before the financial crisis and could indicate that Fitch had at this point already successfully integrated into the oligopoly as a credible player.

The results for 2010-2016 support the view that competition does not lead to rating inflation. Sangiorgi and Spatt (2017) highlight that although competition may cause credit rating agencies to focus on short-term profit, which would result in rating inflation (as discussed by Becker and Milbourn (2011)), competition can simultaneously also counterbalance this by reinforcing the disciplining role of reputation. The threat of potential market share loss originates in the credit rating agencies concern about their future reputation relative to other agencies, as low reputation is more costly under more competitive conditions. We see that Fitch has over time built up a credible reputation, illustrated by being added to the Lehman Index in 2005 and being used as a tiebreaker between S&P and Moody's ratings (Becker and Milbourn, 2011). As Fitch has established their position in the industry by 2010-2016, S&P should be more concerned about their reputation relative to Fitch in this time period than they were in 1995-2006. Decreases in their reputation relative to a more credible actor would lead to a larger discount factor on their future profits, making rating inflation more costly in 2010-2016. This could be why we no longer see a significant correlation between competition and rating quality. Furthermore, our results for 1995-2006 also show that competition only has modest effects on rating quality. Bae et al. (2019) explains that the effects of competition on rating quality for larger rating agencies, such as S&P, might be too small to detect, even if they are present. Taking this into account, as well as that our measures of competition displays low within-industry variation throughout 2010-2016, it could perhaps be expected that we do not identify significant correlations.

The Dodd-Frank Act passed in 2010 after the financial crisis, which in the period 2010-2012 led to rating agencies lowering their bond ratings in response to the threat of legal proceedings (Dimitrov et al. 2015). There is an indication that these effects are also present in our data set, as average firm ratings decreased by 0.255 between our two periods of interest. Dimitrov et al. (2015) further finds that industries with a lower Fitch market share (i.e. less competition) showed an increase in the magnitude of the effect. The incumbent firms faced higher levels of potential legal costs as well as a larger share of potential revenue loss in the more consolidated industries, which provided the incentive to publish relatively lower ratings in order to protect their reputation. The SEC has however since 2012 never taken the steps to fully implement the relevant provisions of the Dodd-Frank Act, and no major lawsuits have been filed in reference to actions by credit rating agencies after the financial crisis (Partnoy, 2017). The lack of action by regulators after the threat of increasing accountability should subsequently lead to credit rating agencies updating their expectations, with less severe effects on future reputation and costs. This should then also diminish the incentive to issue lower ratings of inferior quality in more competitive industries, which is a further explanation for why we do not observe any correlation between S&P rating quality and competition.

There is a further possible mechanism affecting our results. Between the years 2010-2016, markets experienced an overarchingly positive growth, with the S&P 500 index increasing by more than 100 percent, from roughly 1120 to 2230 basis points (S&P Dow Jones Indices, 2020). In periods of expansion, the probability of default of a firm is relatively lower, which makes monitoring credit rating agencies less effective and lessens the chance of legal or reputational repercussions, which can lead to rating inflation (Bar-Isaac and Shapiro, 2013). There is also less pressure to keep ratings low for the sake of preserving reputation when the general economic outlook is positive. Many investors who are restricted in their investment options by regulatory standards or investment guidelines actually demand higher ratings in booms in order to be able to take on additional risk and earn higher returns (Bar-Isaac and Shapiro, 2013). This would indicate that we would observe a decrease in rating informativeness over time, independent of competition, which is not the case in our data. Bar-Isaac and Shapiro (2013) however show in their theoretical model that as a boom persists, the severity of this effect diminishes, as investments in rating quality increase again due to changing expectations. Given that the positive market development persists throughout our data set, this could be why we do not observe decreasing rating informativeness over time. Bar-Isaac and Shapiro (2013) also build on the assumption that agencies are not paid for providing low ratings, as issuers will choose not to issue their debt instrument. This assumption does not hold true for firm ratings, as they will be issued by the rating agency regardless of the input from an issuer and could therefore be a further reason for why we do not find the decrease in rating informativeness in our data.

A further interesting finding is that HH-Index as a measure of competition does not yield results that are as similar to Fitch market share as expected. Replicating the regressions of Becker and Milbourn (2011) with HH-Index shows that it is consistently less significant than Fitch market share. 1995-2006 was a time period in which Fitch grew explosively and became a credible challenger to the incumbents S&P and Moody's. This structural shift therefore seems to be better captured using Fitch market share directly instead of HH-Index. The index also lacks some nuance and cannot distinguish between the causes of different values of the index, i.e. similar values for the index can exist for very different market scenarios.[12] Therefore, even though the value of the index changes in response to Fitch entering the market, it does not provide as clear of a picture of the circumstances as solely Fitch market share. Consequently, we reaffirm that context is important when choosing a measure, and in these early years, the relative market share of S&P and Moody's is perhaps less interesting. In the later time period, the results are insignificant. This outcome makes it difficult to judge whether the index does a better job at describing the state of competition across this time period relative to the earlier one.

[12] For example, a HH-Index value of circa 3000 could be achieved by an industry with one firm with a 50% market share and 5 firms with 10% market shares, but also by an industry with 3 equally sized competitors that each have 31.5% of the market and a single smaller competitor of 5.5%.

6.1 Limitations

There are some clear limitations to our work. Our data shows that in 2010 and onwards, Fitch has a relatively stable year-to-year market share within most industries. There is also an overrepresentation of firm rating observations that come from industry-years with market shares close to the mean market share, which decreases the variance of the market share variable used in the regressions further. This lack of variation increases the uncertainty of our findings as the regressions might not be able to capture the variation in rating level and default rate under different intensities of competition. This implies that Fitch market share might be a weaker proxy for competition than it was previously, which is why we include a second measure of competition, HH-Index. We however find that it actually displays an even lower level of variance than Fitch market share does alone. Of note is that our data still displays cross-industry variation. As previously discussed, revenue should ideally be used to represent market share, as a measure based solely on the number of bond ratings does not account for differences in prices that are solicited by each rating agency. Given that all three rating agencies are private subsidiaries and do not publish this data, true market share is hard to measure to full accuracy. Taking these factors into account, the true effects of competition on rating quality could be more prominent than our findings show due to measurement bias.

Bae et al. (2015) explain that clustering by industry-year can create bias in the estimated standard errors if the time-series correlation in Fitch market share is high. As the variance in Fitch market share has decreased over our time-period and the market shares reached a relatively stable level, the estimated standard errors can appear to be smaller than they actually are. One way to test this is by clustering at industry-level and comparing the resulting standard errors. This requires the number of clusters to be sufficient, as clustered standard errors are also biased when there are too few clusters (Petersen, 2009). Given that we only have 22 industries in the analysis, clustering at industry-level might still lead to biased standard errors. A possible solution is to extend the definition of industries from two-digit to four-digit NAICS codes, which would provide us with approximately 270 industries. However, this increases the uncertainty in the independent variable, as every market share calculation is based on too few bonds to provide an accurate proxy for competition. Becker and Milbourn (2011) also state that the narrower four-digit industries might not be competitively distinct from the perspectives of credit ratings agencies. So, while narrower industries can be used to test clustering at industry-level, it will not be directly comparable to the broader industries due to the above-mentioned reasons. Time series correlation is therefore a potential limitation in our paper.

Lastly, it is important to consider cases of reverse causality or omitted variable bias in the earlier data sample. Although we control for cross-industry and year variation as well as for firm fixed effects and controls, omitted variables may still be present and hard to fully rule out. Furthermore, reverse causality is harder to rule out only by the inclusion of controls. Fitch could have primarily entered markets with generally higher ratings, leading to a correlation between rating level and market share. However, it would be more likely that issuers with lower ratings would demand an additional rating from a new agency, which would instead bias the results of the effect towards zero (Pacces and Romano, 2015). In the context of rating informativeness, there is a risk that Fitch can establish stronger positions in industries neglected by the other incumbent rating agencies by providing lower quality ratings. There is however no reason to expect them to do so, and it also does not explain the findings concerning rating level (Becker and Milbourn, 2011). Becker and Milbourn (2011) also show in their paper through further testing that increased credit demand and information opaqueness are both unlikely omitted variables. Given that the main period of interest in this paper is 2010-2016, in which we do not identify a conclusive correlation between competition and rating quality, we do not consider further cases of reverse causality or omitted variable bias.

7. Conclusions

Research on the relationship between rating quality and competition of rating agencies is inconclusive. Becker and Milbourn (2011) find that there is a significant correlation between these two variables in 1995-2006, in the form of rating inflation by incumbent firms as a reaction to Fitch entering the market. We confirm these findings through a replication of their study and extend their methodology to examine whether these effects are present after the financial crisis and the passing of the Dodd-Frank Act. We find no evidence, when fixed effects and controls are included, that there is a correlation between competition and S&P firm rating quality, quantified in the dimension of rating level and rating informativeness in the years 2010-2016. This holds true even for an additional measure of competition, the HH-Index, which is used to capture any additional nuances in competition stemming from the other large rating agencies. The insignificant relationship can be attributed to Fitch becoming an established and reputable actor within the credit rating industry, which makes rating inflation more costly for S&P. The insignificance of our results can also be understood through both the decline in concern surrounding Dodd-Frank and the persistence of the boom period throughout the entirety of 2010-2016. We can conclude that the insignificance of the correlation is a positive development, as the quality of ratings provided to investors should not vary depending on the level of competition in the rating agency industry. Given the role that credit ratings play in information transfer and signalling, it is clear that any decrease in friction in the determination of ratings is good for financial markets (Stahl and Strausz, 2017).

There are interesting avenues of further extending this research, such as varying the geographic scope of the study. Other regions, such as the European Union, implemented their own legislation after the 2008 financial crisis to amend inefficiencies in the credit rating industry, which could be used to contrast the findings of this paper (European Commission, n.d.). The major rating agencies that exist in the United States are also active market players internationally, often holding majority market shares, which could lead to similar findings, even when the nationally implemented regulatory measures differ (Moody's Analytics, 2019).

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9. Appendix

Appendix 1

Describes how the S&P domestic long-term issuer credit rating is converted into a numerical code. Grades are a cardinal variable measured on a scale from 1 to 28. Each class is assigned three numbers to account for positive and negative grades. Those classes without grades are assigned the midpoint value. Based on the work of Hand et al. (1992) and used by Becker and Milbourn (2011). The source for category definition is S&P Global (2019).

Grade	Rating agency	Numerical code	Category definition
	S&P		
Investment grade	AAA	28	An obligor has extremely strong capacity to meet its financial commitments.
Investment grade Investment grade Investment grade	AA+ AA AA-	26 25 24	An obligor has very strong capacity to meet its financial commitments. It differs from the highest-rated obligors only to a small degree.
Investment grade Investment grade Investment grade	A+ A A-	23 22 21	An obligor has strong capacity to meet its financial commitments but is somewhat more susceptible to the adverse effects of changes in circumstances and economic conditions.
Investment grade Investment grade Investment grade	BBB+ BBB BBB-	20 19 18	An obligor has adequate capacity to meet its financial commitments. However, adverse economic conditions or changing circumstances are more likely to weaken the obligor's capacity to meet its financial commitments.
Speculative grade Speculative grade Speculative grade Speculative grade Speculative grade Speculative grade Speculative grade Speculative grade Speculative grade Speculative grade Speculative grade	BB+ BB BB- B+ B B- CCC+ CCC CCC- CC C	17 16 15 14 13 12 11 10 9 7 4	Obligors rated 'BB', 'B', 'CCC', and 'CC' are regarded as having significant speculative characteristics. While such obligors will likely have some quality and protective characteristics, these may be outweighed by large uncertainties or major exposure to adverse conditions.[13]
Default	SD/D	1	A 'D' rating is assigned when S&P believes that the default will be a general default and that the obligor will fail to pay all or substantially all of its obligations as they come due. An 'SD' rating is assigned when S&P believes that the obligor has selectively defaulted on a specific issue or class of obligations, but it will continue to meet its payment obligations on other issues or classes of obligations in a timely manner.

[13] The 'C' rating is no longer included in the scale by S&P. Only one observation in our data set is assigned a C rating in 1995.

Appendix 2

Two-digit NAICS codes and the respective industry name. Annual mean for Fitch market share and HH-Index for respective industry is shown for our two sample periods. The market shares and HH-Indexes for 1995-2006 are calculated including bond affirmations and for 2010-2016 bond affirmations are excluded.

NAICS	Industry name	Fitch market share		HH-Index	
		1995-2006	2010-2016	1995-2006	2010-2016
11	Agriculture, Forestry, Fishing and Hunting	0.17	0.23	0.399	0.377
21	Mining, Quarrying, and Oil and Gas Extraction	0.22	0.19	0.364	0.374
22	Utilities	0.31	0.24	0.347	0.362
23	Construction	0.19	0.25	0.396	0.352
31	Manufacturing: Food, Textile, Apparel	0.24	0.23	0.368	0.356
32	Manufacturing: Wood, Paper, Printing, Petroleum, Chemicals, Plastics	0.20	0.20	0.372	0.364
33	Manufacturing: Metals, Machinery, Computers, Electrical, Furniture	0.22	0.24	0.364	0.351
42	Wholesale Trade	0.20	0.22	0.373	0.361
44	Retail Trade: Motor Vehicles, Furniture, Electronics, Food, Gas	0.18	0.23	0.388	0.355
45	Retail Trade: Sporting goods, Books, Florists, Office Supplies, Mail-Order, Vending	0.30	0.26	0.364	0.358
48	Transportation and Warehousing: Air Transport, Water Transport, Trucks, Pipelines	0.14	0.18	0.422	0.380
49	Transportation and Warehousing: Messengers, Storage	0.14	0.20	0.452	0.398
51	Information	0.23	0.24	0.363	0.354
52	Finance and Insurance	0.33	0.26	0.346	0.345
53	Real Estate and Rental and Leasing	0.25	0.23	0.368	0.360
54	Professional, Scientific, and Technical Services	0.22	0.20	0.368	0.379
55	Management of Companies and Enterprises	0.25	0.22	0.369	0.357
56	Administrative and Support and Waste Management and Remediation Services	0.21	0.23	0.386	0.368
61	Educational Services	0.25	0.30	0.466	0.425
62	Health Care and Social Assistance	0.21	0.25	0.379	0.359
71	Arts, Entertainment, and Recreation	0.19	0.22	0.373	0.384
72	Accommodation and Food Services	0.21	0.26	0.383	0.352
81	Other Services (except Public Administration)	0.16	0.15	0.399	0.421
92	Public Administration	0.25	0.28	0.378	0.340

Appendix 3

Model specification of the ordinary least square regressions that are used in our research. Only new variables are defined in each regression.

Regressions on rating level

Regression 1

$$(1)\ R_{i,k} = \beta_0 + \beta_1 Competition_{i,j} + \varepsilon$$

Where:
$R_{i,k}$ = Firm long-term credit rating for a firm *k* in a specific year *i*
$Competition_{i,j}$ = Fitch's market share or HH-Index for a specific year *i* and industry *j*

Regression 2

$$(2)\ R_{i,k} = \beta_0 + \beta_1 Competition_{i,j} + \beta_2 Year_i + \beta_3 Industry_j + \varepsilon$$

Where:
$Year_i$ = Annual time dummy variable for a specific year *i*
$Industry_j$ = Industry dummy variable for a specific industry *j*

Regression 3

$$(3)\ R_{i,k} = \beta_0 + \beta_1 Competition_{i,j} + \beta_2 Year_i + \beta_3 Firm_k + \beta_4 Controls_{i-1,k} + \varepsilon$$

Where:
$Firm_k$ = Firm dummy variable for a specific firm *k*
$Controls_{i-1,k}$ = Combined term for the 18 firm-specific accounting variables (see Table 1 for the full list), for each firm *k* at the end of the previous fiscal year *i*-1

Regression 5

$$(4)\ ColR_{i,j} = \beta_0 + \beta_1 Competition_{i,j} + \beta_2 Year_i + \beta_3 Industry_j + \beta_4 ColControls_{i,j} + \varepsilon$$

Where:
$ColR_{i,j}$ = Firm long-term credit ratings collapsed by mean per year *i* and industry *j*
$ColControls_{i,j}$ = Combined term for the 18 firm-specific accounting variables (see Table 1 for the full list), collapsed by mean per year *i* and industry *j*

Regression 6

$$(5)\ ColMR_{i,j} = \beta_0 + \beta_1 Competition_{i,j} + \beta_2 Year_i + \beta_3 Industry_j + \beta_4 ColMControls_{i,j} + \varepsilon$$

Where:
$ColMR_{i,j}$ = Firm long-term credit ratings collapsed by median per year *i* and industry *j*
$ColMControls_{i,j}$ = a combined term for the 18 firm-specific accounting variables (see Table 1 for the full list), collapsed by median per year *i* and industry *j*

Regressions on rating informativeness

Regression 1 & 2

$$(2)\ D_{i,k} = \beta_0 + \beta_1 Competition_{i,j} + \beta_2 Rating_{i,k} + \beta_3 Competition_{i,j} * Rating_{i,k} + \varepsilon$$

Where:
$D_{i,k}$ = Dummy variable for a firm *k* in a specific year *i* defaulting within a three-year horizon
$Rating_{i,k}$ = Investment grade dummy or firm long-term credit rating for a firm *k* in a specific year *i*

Regression 3

$$(3)\ D_{i,k} = \beta_0 + \beta_1 Competition_{i,j} + \beta_2 Rating_{i,k} + \beta_3 Competition_{i,j} * Rating_{i,k} + \beta_4 Year_i + \beta_5 Industry_j + \beta_6 Controls_{i-1,k} + \varepsilon$$

Regression 4

$$(4)\ D_{i,k} = \beta_0 + \beta_1 Competition_{i,j} + \beta_2 Rating_{i,k} + \beta_3 Competition_{i,j} * Rating_{i,k} + \beta_4 Year_i + \beta_5 Industry_j + \beta_6 Year_i * Rating_{i,k} + \beta_7 Industry_j * Rating_{i,k} + \varepsilon$$

Regression 5

$$(5)\ ColD_{i,j} = \beta_0 + \beta_1 Competition_{i,j} + \beta_2 ColRating_{i,j} + \beta_3 Competition_{i,j} * ColRating_{i,j} + \beta_4 Year_i + \beta_5 Industry_j + \beta_6 ColControls_{i,j} + \varepsilon$$

Where:
$ColD_{i,j}$ = Fraction of firms identified as defaulting within a three-year horizon (collapsed by mean) per year *i* and industry *j*
$ColRating_{i,j}$ = Firm long-term credit ratings collapsed by mean per year *i* and industry *j*

Appendix 4

In the table below, firm credit rating (S&P Domestic Long-Term Issuer Credit Rating) is regressed on Fitch market share. The dependent variable, firm credit rating, is based on a numerical scale, ranging from 1 (D) to 28 (AAA). Fitch market share is the fraction of bonds rated by Fitch in an industry-year cell. Firm controls include 18 firm-specific accounting measures. Industries refers to two-digit NAICS codes. In Column 5 and 6 data is collapsed, using mean and median, on industry-year level. Standard errors are clustered at industry-year level, except in Column 5 and 6. All standard errors are heteroskedasticity-robust and shown in parentheses. Intercepts are not reported. Significance level is reported as *** representing 1%, ** 5%, * 10%.

Replication 2000-2006	Dependent variable: firm credit rating					
	OLS (1)	OLS (2)	OLS (3)	Ordered Probit (4)	OLS average by cell (5)	OLS median by cell (6)
Fitch Market Share	6.101***	0.351	0.312	0.075	0.825	-1.423
	(2.072)	(0.726)	(0.479)	(0.171)	(0.612)	(1.280)
Year Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	Yes	No	Yes	Yes	Yes
Firm Fixed Effects	No	No	Yes	No	No	No
Firm Controls	No	No	Yes	No	Yes	Yes
R squared	0.013	0.125	0.902	n/a	0.970	0.954
Number of Observations	12,572	12,572	12,572	12,572	116	116

Appendix 5

In the table below, firm credit rating (S&P Domestic Long-Term Issuer Credit Rating) is regressed on Fitch market share or HH-Index. The dependent variable, firm credit rating, is based on a numerical scale, ranging from 1 (D) to 28 (AAA). Fitch market share is the fraction of bonds rated by Fitch in an industry-year cell. HH-Index is the sum of the squares of the market share of each rating agency in an industry-year cell, divided by 10,000. Bond affirmations are excluded from market share calculations. Firm controls include 18 firm-specific accounting measures. Industries refers to two-digit NAICS codes. In Column 5 and 6 data is collapsed, using mean and median, on industry-year level. Standard errors are clustered at industry-year level, except in Column 5 and 6. All standard errors are heteroskedasticity-robust and shown in parentheses. Intercepts are not reported. Significance level is reported as *** representing 1%, ** 5%, * 10%.

Replication 1995 - 2006 Removing affirmations	Dependent variable: firm credit rating					
	OLS (1)	OLS (2)	OLS (3)	Ordered Probit (4)	OLS average by cell (5)	OLS median by cell (6)
Fitch Market Share	3.566**	1.106*	1.044***	0.263	1.226***	-0.330
	(1.600)	(0.653)	(0.379)	(0.163)	(0.391)	(0.863)
Year Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	Yes	No	Yes	Yes	Yes
Firm Fixed Effects	No	No	Yes	No	No	No
Firm Controls	No	No	Yes	No	Yes	Yes
R squared	0.005	0.139	0.882	n/a	0.966	0.934
Number of Observations	20,343	20,343	20,343	20,343	188	188
HH-Index 1995-2006 - Removing affirmations						
HH-Index	-5.968*	-3.315**	-1.684**	-0.806**	-2.399**	2.011
	(3.432)	(1.547)	(0.810)	(0.390)	(1.122)	(1.995)
Year Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	Yes	No	Yes	Yes	Yes
Firm Fixed Effects	No	No	Yes	No	No	No
Firm Controls	No	No	Yes	No	Yes	Yes
R squared	0.002	0.139	0.881	n/a	0.966	0.934
Number of Observations	20,342	20,342	20,342	20,342	188	188

Appendix 6

In the table below, coefficient estimates are shown from five OLS-regressions. The dependent variable is a dummy variable for firm default (one if a firm is defaulted within the subsequent three years, zero otherwise) which is regressed on Fitch market share (or HH-Index), a credit rating term, and the interaction of Fitch market share (or HH-Index) with the credit rating term. Control variables include industry and year fixed effects, 18 firm-specific accounting measures, as well as interactions between credit rating and year/industry fixed effects. Bond affirmations are excluded from market share calculations. Industries refers to two-digit NAICS codes. In Column 5 data is collapsed, using mean, at industry-year level. Standard errors are clustered at industry-year level, except in Column 5. All standard errors are heteroskedasticity-robust and shown in parentheses. Intercepts are not reported. Significance level is reported as *** representing 1%, ** 5%, and * 10%.

Replication default tests using Fitch market share 1995-2005	Dependent: Default within three years				
Removing affirmations	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS averaged by industry-year (5)
IG-dummy*Fitch market share	0.049				
	(0.054)				
IG dummy	-0.050***				
	(0.011)				
Credit rating*Fitch market share		0.010	0.009	0.009	-0.003
		(0.008)	(0.006)	(0.008)	(0.008)
Credit rating		-0.010***	-0.012***	-0.008	0.0002
		(0.002)	(0.002)	(0.005)	(0.007)
Fitch market share	-0.024	-0.177	-0.143	-0.143	0.044
	(0.052)	(0.155)	(0.120)	(0.165)	(0.158)
Year Fixed Effects	No	No	Yes	Yes	Yes
Industry Fixed Effects	No	No	Yes	Yes	Yes
Year Fixed Effects*Credit rating	No	No	No	Yes	No
Industry Fixed Effects*Credit rating	No	No	No	Yes	No
Firm Controls	No	No	Yes	No	Yes
R-squared	0.017	0.044	0.073	0.081	0.563
Number of Observations	18,549	18,549	18,548	18,549	242
Default tests using HH-Index 1995-2005 - Removing affirmations					
IG-dummy*HH-Index	-0.197				
	(0.121)				
IG dummy	0.034				
	(0.047)				
Credit rating*HH-Index		-0.038*	-0.037**	-0.035*	-0.017
		(0.019)	(0.017)	(0.020)	(0.026)
Credit rating		0.007	0.004	0.008	0.008
		(0.007)	(0.006)	(0.010)	(0.014)
HH-Index	0.183	0.745*	0.681**	0.662*	0.350
	(0.117)	(0.382)	(0.314)	(0.392)	(0.518)
Year Fixed Effects	No	No	Yes	Yes	Yes
Industry Fixed Effects	No	No	Yes	Yes	Yes
Year Fixed Effects*Credit rating	No	No	No	Yes	No
Industry Fixed Effects*Credit rating	No	No	No	Yes	No
Firm Controls	No	No	Yes	No	Yes
R-squared	0.018	0.045	0.074	0.081	0.564
Number of Observations	18,548	18,548	18,547	18,548	241